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ORIGINAL PAPER

Implementation and integrated numerical modeling of a landslide early warning system: a pilot study in Colombia

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Abstract Landslide early warning systems (EWS) are an important tool to reduce landslide risks, especially where the potential for structural protection measures is limited. However, design, implementation, and successful operation of a landslide EWS is complex and has not been achieved in many cases. Critical problems are uncertainties related to landslide triggering conditions, successful implementation of emergency protocols, and the response of the local population. We describe here the recent implementation of a landslide EWS for the Combeima valley in Colombia, a region particularly affected by landslide hazards. As in many other cases, an insufficient basis of data (rainfall, soil measurements, landslide event record) and related uncertainties represent a difficult complication. To be able to better assess the influence of the different EWS components, we developed a numerical model that simulates the EWS in a simplified yet integrated way. The results show that the expected landslide-induced losses depend nearly exponentially on the errors in precipitation measurements. Stochastic optimization furthermore suggests an increasing adjustment of the rainfall landslide-triggering threshold for an increasing observation error. These modeling studies are a first step toward a more generic and integrated approach that bears important potential for substantial improvements in design and operation of a landslide EWS.

Keywords Landslides · Early warning systems · Earth observation · Uncertainties · Integrated modeling

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1 Introduction

Early warning systems (EWS) for natural hazards are important tools for disaster risk reduction. EWS have been developed for a number of different hazards, including tsunamis, volcanoes, snow avalanches, landslides, and others (Zschau and Küppers 2003). EWS commonly consist of different components, such as (i) sensors measuring geophysical, atmospheric, hydrodynamic, and soil-related parameters, (ii) telecommunication equipment transmitting the data to a (iii) monitoring and analysis center, (iv) decision procedures and organizational structures that facilitate the translation of the technical data into publicly understandable information, and (v) response of people, which may be affected. The awareness and knowledge of the people exposed to a hazard are very important for their adequate response to an early warning. As such, EWS have in fact increasingly been recognized as highly complex systems ultimately characterized by a tricky interaction between technical instruments and human behavior (Sorensen 2000; Basher 2006). Each EWS component has a certain potential for failure that determines whether the system eventually is successful or not. Due to the uncertainties related to the different procedures, a systematic evaluation of EWS is rather complicated.

We present here an approach to numerically model a landslide EWS that enables us to systematically assess the influence of the different EWS components on the overall performance and success of the system, including, for instance, climatically related changes, sensor related modifications, or changes in the human behavior.

We developed our model based on a recently installed landslide EWS in Colombia. Landslides are notorious in Colombia due to the rough topography and tropical rainfall conditions and thus are a major hazard in many regions of the country. The Combeima region, Tolima province, is a particularly exposed area, including several population centers along the valley and the regional capital Ibagué (ca. 0.5 million inhabitants). Hundreds of people have been killed by landslides and debris flows in the past. Most recently, multiple slope failures and landslides destroyed major parts of population centers in June 2006. These recurring events are therefore a serious threat to life, welfare, and local economy. So far, activities have mainly been focused on reconstruction after disasters, and prevention and preparedness activities have not been sufficiently developed. The landslide EWS has been designed and implemented within a Colombian-Swiss project funded by the Swiss Agency for Development and Cooperation (SDC) and is currently being calibrated and adjusted.

The integrated EWS model described in this article represents a novel approach and we therefore had to simplify several components of the real EWS. Nevertheless, it should be able to provide indications on how the EWS in the Combeima region could be improved in the future. Although the model is driven by data from this case study, the model concept is designed sufficiently open for adaptation to other landslide EWS.

2 EWS in Colombia

2.1 Study area

The Combeima river is one of the major drainages of the Nevado del Tolima Volcano, located in central Colombia in the Cordillera Central. The Combeima valley extends from the regional capital Ibagué ($\sim$500,000 inhabitants) at 1,250 m asl along more than 20 km to about 2,500 m asl before it abruptly rises to the summit of Nevado del Tolima at

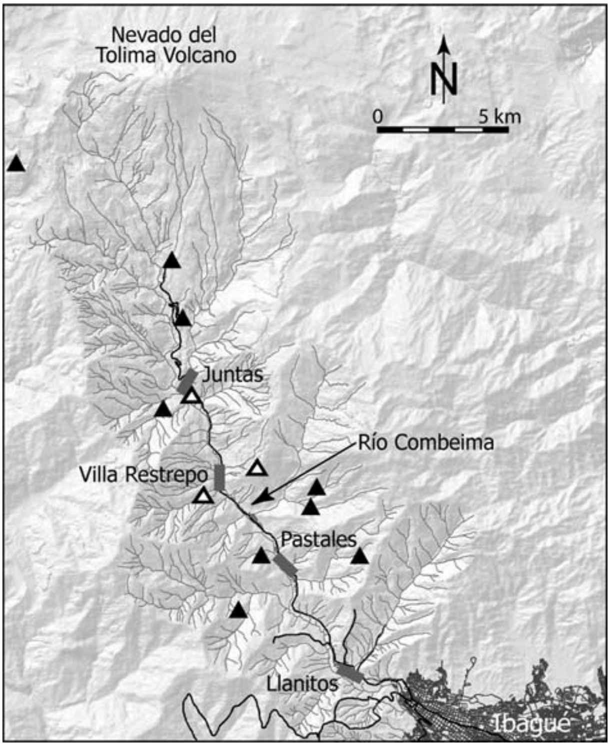

Fig. 1 Map and stream flow system of the Combeima valley. *Triangles* indicate locations with rainfall stations (only partly operational), with *white triangles* referring to new telemetric rainfall stations that form part of the landslide EWS

5,200 m asl. Several towns populate the Combeima valley, with a total of about 5,500 people (Fig. 1). The area is characterized by very steep topography and dense vegetation. Mean annual rainfall varies between 1,500 and 2,500 mm. The geology is dominated by the volcanic activity of the area. Two major active volcanoes, Tolima and Machín volcano, are located within distances of 10 to 20 km and have repeatedly erupted during the Holocene (Thouret et al. 1995). As a consequence, the soils of the steep slopes of the Combeima valley are often characterized by a high content of ash and other volcanic products, partly with underlying metamorphic rocks. Geotechnical soil parameters are typically characterized by poor slope stability. Lahars and pyroclastic density currents from the Tolima volcano repeatedly swept through the valley during the past few thousand years, at least partly caused by interaction between volcanic activity and glacier ice on top of the volcano (Cepeda and Murcia 1988; Huggel et al. 2007).

Despite the steepness, the slopes are intensively cultivated in the lower sections by crops such as coffee, banana, maize, and others. Grazing by livestock is also widespread. Illegal burning of densely vegetated slopes for agricultural purposes is a serious problem, both in terms of uncontrolled forest fires and slope destabilization.

Steep topography, high rainfall intensities, and poor slope stability make the Combeima valley particularly vulnerable to landslides. In fact, people have suffered from landslide disasters for many decades (Godoy et al. 1997). Also, landslide events often occur in combination with flooding of the Combeima River with occasional process interaction such as blocking of the main river by landslide and debris flow material transported by tributaries. Figure 2 shows the chronology of landslide disasters in the Combeima valley for the last 50 years. Up to several hundred people were killed in single events, and damage to

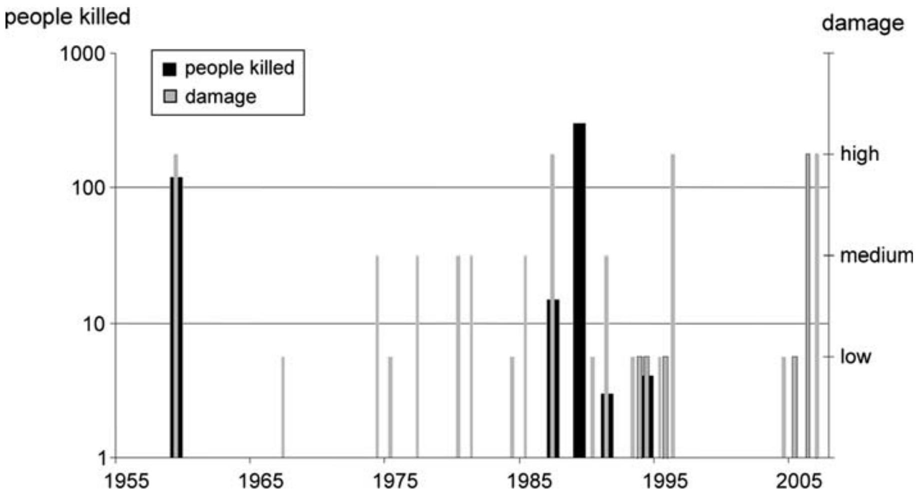

Fig. 2 Chronology of landslide disasters in the Combeima valley, distinguishing number of people killed and a qualitative measure of damage

residential areas and infrastructure has often been severe. The last major disaster occurred in June 2006, affected extended parts of the valley, and stroke the town of Villa Restrepo particularly hard (Fig. 3). In consideration of the magnitude and extent of the landslides and debris flows, it was very fortunate that no people were killed. Alerted by the sound of the rising tributaries, people could gather at safe places and avoid the violent impact of the debris flows.

2.2 Rainfall records

Rainfall measuring stations are a key component of a landslide EWS. In the Combeima valley, the first rainfall station was installed in the late 1950s. The bulk of stations existing today came into operation in the 1980s. Stations are operated by the Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM) and data are centrally managed in Bogotá. The IDEAM network currently includes ten stations in the Combeima valley (Fig. 1). The rainfall recording is continuous on daily charts, which can be evaluated to intervals as low as 15 min. In January 2008, three telemetric stations were installed which can be programmed to transmit measured data when a rainfall increment occurs (i.e., 0.2 mm) or at a fixed time interval. Although the older rainfall gauges in the Combeima had a comparably high density, their use for a landslide EWS was limited because most of the stations are not telemetric and charts data are collected about every month. However, the data is valuable for ex post analysis of rainfall characteristics of the Combeima valley, and to relate rainfall to observed landslide events in the past.

For all stations, available rainfall records were analyzed, and rainfall intensities calculated based on 15-min recording intervals. This is a laborious work because several stations' data were not yet digitally stored and rainfall events had to be detected manually. Based on this analysis, rainfall intensity-duration frequency (IDF) curves per station were computed using SIAT, a specialized software tool (Ramírez 2007). For each rainfall station, the system reads the mass curve (time-accumulated rainfall) for every storm and computes intensities for user selected time periods (15, 30, 60, 120, 360 min). After

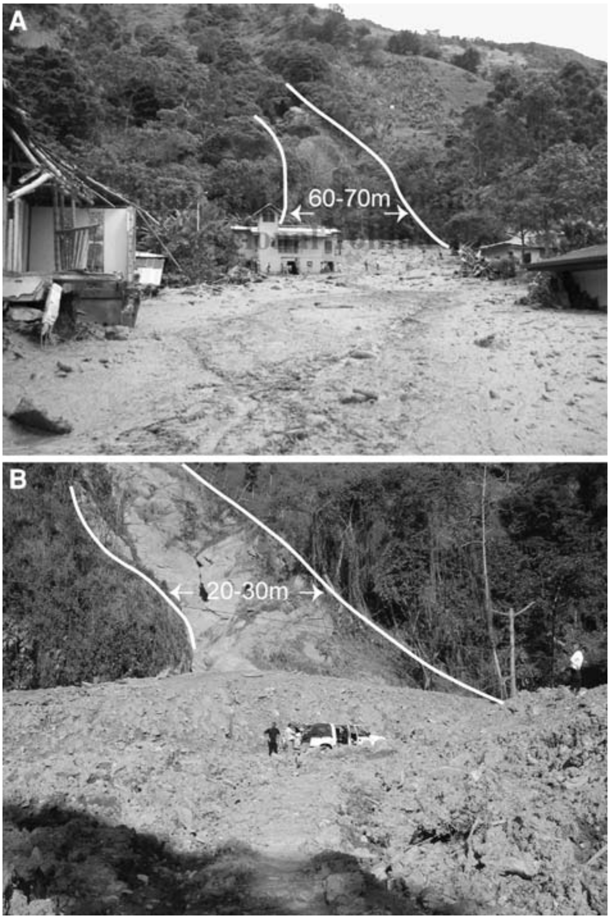

Fig. 3 Landslide disaster in the Combeima Valley in June 2006. **a** Devastated residential buildings in Villa Restrepo, and **b** debris flow channel and deposits obstructing the Combeima highway between Villa Restrepo and Juntas. Deposits height is in the order of 5 m (see car and persons for reference). The *solid lines* mark the trimlines of the debris flow channels and indicate the extremely large flow discharge. For the Villa Restrepo event, flow discharge is estimated at 300–400 m^3/s while normal discharge of the stream is less than 1 m^3/s (photos taken by **a** Colombian Red Cross and **b** C. Huggel)

reading all the storms for the station, the system defines for every time duration the maximum intensity for every year. Finally, a frequency distribution method is applied to obtain intensity-return period pairs for the given time duration.

The longest rainfall records for single stations were close to 20 years. Figure 4 shows two IDF curves for the stations "Placer" and "Palmar." They are located approximately at the same elevation of $\sim$2,200 m asl but "Palmar" some 8.5 km up-valley toward Tolima Volcano. The analysis of the IDF curves suggests that the stations further downstream and further away from the Tolima Volcano have higher rainfall intensities. For instance, while the lower stations show a rainfall intensity of slightly less than 100 mm/h for a duration of 1 h and a 100-year return period, stations located further up-valley feature corresponding rainfall intensities reduced by $\sim$30%.

Due to data limitations, it was not possible to relate IDF curves to observed landslide events to derive landslide-triggering rainfall thresholds (Glade et al. 2000; Guzzetti et al. 2008). However, daily rainfall data could be used to analyze antecedent rainfall conditions for a number of documented landslides. The about 20 landslide events on record often caused severe damage and destruction to local communities (Figs. 2, 3). Daily rainfall was analyzed up to 30 days prior to the landslide events, and for the station(s) closest to the

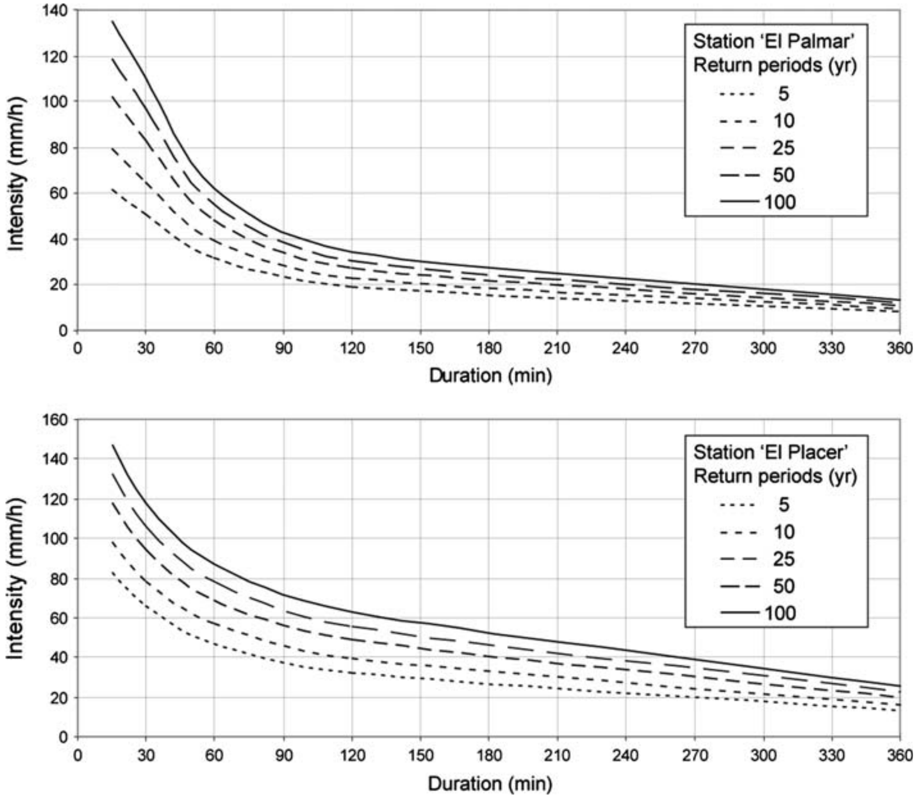

Fig. 4 Intensity-duration curves for rainfall stations "Placer" and "Palmar"

landslide initiation area. Figure 5 shows antecedent rainfall for all landslide events for which reasonably reliable relations to rainfall data could be established. The range of variability of landslide-triggering antecedent rainfall thresholds is considerable. As a first threshold indicator, 25-, 50-, 75-, and 90-quantiles of antecedent rainfall were calculated. In addition, the landslide records were evaluated in terms of their reliability of information provided, e.g., how precisely the landslide location could be identified, and the distance of the closest rain gauge to the landslide. Based on this, three classes of reliability of antecedent rainfall conditions (Fig. 5) were distinguished and helped to define warning levels for the EWS.

2.3 Implementation of EWS and related challenges

The magnitude and frequency of landslide disasters occurring in the Combeima valley have urgently called for an improved risk reduction. Structural protection measures are often not feasible due to financial restrictions. Organizational and preparedness measures such as EWS or emergency training have therefore been in the focus. Within a joint Colombian-Swiss Government project, the implementation of EWS has been a major objective.

However, the appropriate implementation and operation of a landslide EWS is a complex task and only few examples can be found worldwide. Probably, the earliest

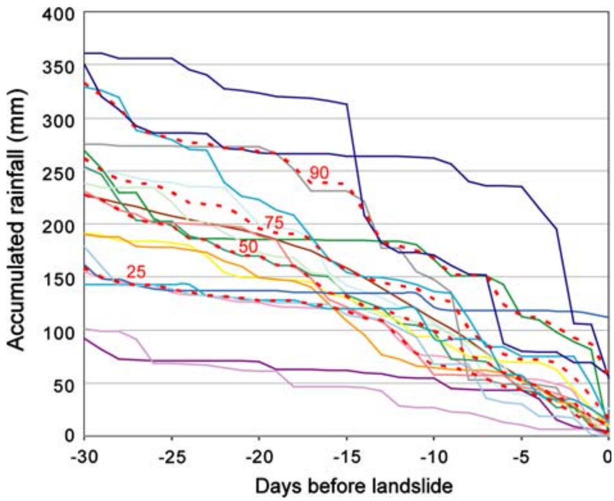

Fig. 5 Antecedent rainfall for documented landslide events between 1974 and 2006 in the Combeima valley. The graph shows the large variability of existing rainfall conditions triggering landslides. *Dashed lines* and corresponding numbers indicate 25, 50, 75, and 90% quantiles

landslide EWS was developed in the San Francisco Bay region (USA) in the mid-1980s and consisted of a real-time network of rain gauges, precipitation forecasts, and relations between rainfall and landslide initiation to define the alert level (Keefer et al. 1987). The relation between rainfall and landslide occurrence, or in more general terms, the understanding when, why, and how large landslides occur is an important basis for EWS. A number of physical models were developed that describe the mechanics of material strength, gravitational stress, pore-fluid pressure, and external forces (e.g., Iverson et al. 1997; Petley et al. 2005). A major drawback to apply physical–mechanical models for landslide EWS is the great variability of properties of soil and earth materials and slope conditions that make the prediction of when and where a landslide occurs very difficult. Therefore, empirical relations between rainfall duration or intensity and landslide initiation are typically applied for EWS. These relations need to be established by a record of landslide-triggering rainfall events. Several relations have been presented for different regions worldwide (Guzzetti et al. 2008), but are mostly lacking for Colombia so far (Terlien 1998). Due to the strong variability of rainfall and soil conditions, it is indispensable to develop a rainfall–landslide relation adapted to the region where the EWS is about to be implemented.

The spatial variability of rainfall and incomplete event description induce an uncertainty into the rainfall–landslide triggering threshold. It is essential that this uncertainty is adequately managed in EWS and efforts are put to reduce it. The need to improve the rainfall monitoring in the area by having automatic real-time rainfall gauges for EWS purposes gave reason to install three new rainfall gauges at sites located closer to the landslide initiation zones. The large variability of antecedent rainfall observed for past landslide events (Fig. 5) makes the definition of warning thresholds difficult. In a test phase of the EWS, quantiles were used to define increasing levels of landslide hazard. In order to further reduce the uncertainties, the rainfall stations were equipped with geophones that transmit increasing debris flow activity in the stream channels. A third control is achieved by local observers that report potentially landslide-producing situations timely to the EWS

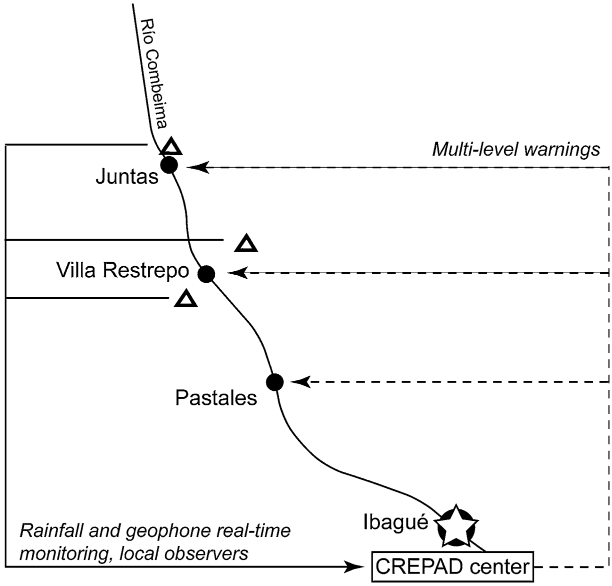

Fig. 6 Schematic structure of the landslide EWS in the Combeima region. *Triangles* denote recently installed rainfall and geophone monitoring stations. For the sake of clarity, not all local communities of the Combeima valley are included. CREPAD is the Regional Emergency Committee of Tolima

center in Ibagué (Fig. 6). At this center, which is hosted at the Regional Emergency Committee of Tolima (CREPAD), all available information is analyzed 24 h a day. Rainfall and geophone measurements are transmitted in real-time to an internet application and CREPAD operators or other potential users can directly consult with the internet to determine whether a rainfall–landslide threshold is reached. An emergency protocol defines the different levels of warning and the corresponding actions to be taken.

The EWS is only successful if it is also accepted, understood, and used by the local population. Even though the technical side of the EWS is complex, the greatest potential for failure exists if the local population is inadequately prepared for emergencies. Therefore, preparedness and social programs have been carried out in the Combeima region. These studies are, however, beyond the scope of this article, and will not be discussed here in further detail.

3 A numerical EWS model

3.1 Rationale for the approach

Design and implementation of the landslide EWS prompted a number of essential questions that are closely linked to the success of the system:

- What is the effect of errors in rainfall measurements on the reliability of a landslide EWS?
- How can uncertainties related to landslide-triggering rainfall thresholds be better handled in an operational EWS?
- How do the above points influence the impacts and consequences of landslide events?

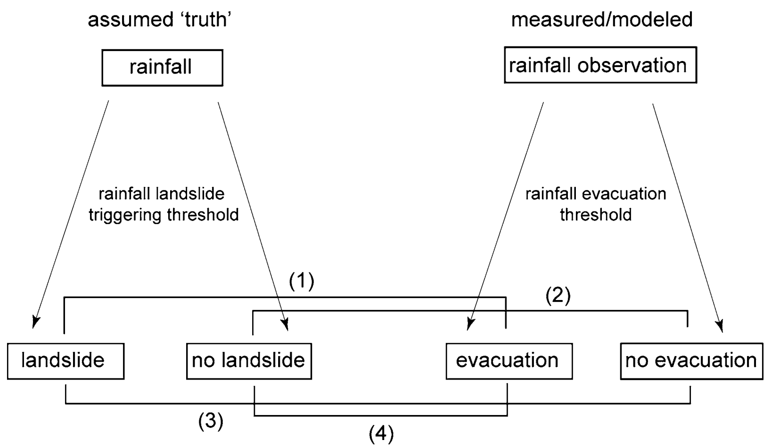

Fig. 7 Scheme demonstrating the essential components of the landslide EWS model. (1–4) represent four different scenarios for which damage estimates are calculated in the model: (1) damage to buildings and evacuation cost; (2) no cost; (3) damage to buildings and loss of lives; (4) evacuation cost

This may likely not be a complete list of essential questions related to the implementation and operation of a landslide EWS but it touches aspects of fundamental importance. These questions cannot definitely be answered by experience or by trial-and-error but need a more systematic approach. Here, we present a model based on a stochastic optimization approach, which is novel in its application for a landslide EWS. The model basically mimics different components of a landslide EWS, including the relations and criteria that link these components (Fig. 7). Obviously, the model requires several simplifications of the reality, which in our case, partly stem from limitations of the data. Methods, including the necessary simplifications, and applied data are presented in the following for each component of the model.

3.2 Observations: rainfall input data

Although there exists a rainfall record from several rain gauges in the Combeima valley (as outlined above), there are a number of limitations regarding complete data series over many years at temporal resolutions better than daily ones. Therefore, instead of local rain gauges, we used ERA-40 reanalysis rainfall data from the grid cell closest to the Combeima valley. ERA-40 is a reanalysis of meteorological observations from 1957 to 2002 produced and provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) in collaboration with other institutions (Uppala et al. 2005). The spatial resolution of ERA-40 data is 2.5°, and the center point of the grid cell used here is located about 60 km northeast of the Combeima valley. The temporal resolution of the rainfall data is 6 h.

It is clear that the rainfall conditions in the Combeima valley cannot be exactly represented by the ERA-40 reanalysis data but elevation and topographic conditions are similar. Furthermore, it has been observed that rainfall has a considerable variability even within the Combeima catchment. The use of a single point rain gauge data to be related to observed landslides over larger areas of the Combeima would therefore not be feasible. Due to these currently existing data restrictions, we refrained from directly verifying the ERA-40 reanalysis data with observed landslide events.

3.3 Intensity-duration threshold (LS—triggering)

Generally speaking, the landslide research has developed two different basic approaches to predict rainfall triggered landslides: physically based and empirically based models. Physically based models try to mimic the physical processes relevant to landslide initiation to determine landslide occurrence in space and time. Many physically based landslide models have been developed over the last years, and examples can be found, for instance, in Montgomery and Dietrich (1994), Iverson (2000), or Crosta and Frattini (2003). For use in EWS, a clear limitation of physically based models is the demand for detailed spatial information, including hydrological, lithological, morphological, and soil characteristics that control the initiation of landslides. These data are barely available over areas larger than specific test sites.

Empirically based models statistically relate rainfall parameters such as intensity and duration to observed landslide events. Rainfall intensity is commonly given in millimeters per hour and may be measured over shorter or longer periods, and correspondingly, has different physical implications (Wieczorek and Glade 2005; Guzzetti et al. 2007). Most commonly, the rainfall parameters intensity I (mm/h) and duration D (h) have been used to derive landslide-triggering thresholds based on observed events. Such thresholds have been developed for global (e.g., Caine 1980), regional (e.g., Larsen and Simon 1993) and local applications (e.g., Marchi et al. 2002). The threshold is usually expressed in the form:

$$I = aD^b \tag{1}$$

where a and b are empirical parameters.

Due to the limitations of physically based approaches for use in EWS, we implemented an empirically based threshold function in our model. We thereby consider a time period of 10 years split into smaller intervals of 6 h each. In the absence of any regional or local threshold available for our study region in Colombia, we used the Caine (1980) global threshold. The triggering threshold we used to model landslide occurrence is then described by a binary-valued function:

$$L(i) = \begin{cases} 1, & \text{if } \max\limits_{0 \le j \le 19} (I_{ij} - \tilde{I}_j) \ge 0, \\ 0, & \text{else.} \end{cases} \tag{2}$$

Here, $\tilde{I}_j = 14.82[6(j+1)]^{-0.39}, \quad j = 0, \ldots, 19$ are triggering intensities for time intervals ranging from 6 to 120 h, $i \ge 20$ is the number of a 6-h interval within the whole 10-year time period. Values $\{I_{ij}\}$ are calculated intensities: $I_{ij} = \frac{1}{6(j+1)} \sum_{k=0}^{j} r_{(i-k)}$ for rainfall data $\{r_i\}$. The value 1 of the function $L(i)$ represents a landslide occurrence in the ith time frame, whereas value 0 means no landslide in the ith time frame.

3.4 Observation errors and evacuation threshold

In (2), exact values of rainfall are used to calculate intensities I_{ij}. In reality, the exact precipitation is not known; instead, its value is measured with some error. In fact, quality and precision of measured rainfall data is a notorious problem for use in landslide models and early warning systems. We therefore intentionally introduced errors into the original ERA-40 rainfall data to assess corresponding effects on evacuation and damage. When simulations are run with degraded datasets of rainfall, the original ERA-40 data is taken as the control data, and it is assumed that the ERA-40 data perfectly represents the rainfall conditions at the local landslide site (Fig. 7).

We therefore model rainfall measurement error for each time frame i by means of random value generation distributed uniformly in the interval $[r_i - \varepsilon\, r_i,\ r_i + \varepsilon\, r_i]$ where ε is a constant rainfall measurement error with its value fixed in the interval [0, 0.3] for the purposes of numerical simulations.

Given exact rainfall information, one could use the threshold function (2) for evacuation. Here, for the sake of simplicity, we assume that upon reaching a triggering threshold in (2), an evacuation is performed within a "short enough" time frame, meaning before a landslide actually occurs. This assumption allows us to avoid substantial complications in the model related to rainfall forecasting. Taking into account rainfall measurement errors, a threshold for evacuation from a dangerous area should be adjusted. The idea is to decrease the original landslide-triggering threshold by multiplying it with the correction coefficient $\lambda \in (0, 1)$. The evacuation threshold function based on (2) is defined by the following expression

$$V(i,\lambda) = \begin{cases} 1, & \text{if } \max\limits_{0 \le j \le 19} (\hat{I}_{ij} - \lambda \tilde{I}_j) \ge 0, \\ 0, & \text{else.} \end{cases} \tag{3}$$

where $\hat{I}_{ij}$ are intensities calculated for observed rainfall

$$\hat{r}_i \sim U(r_i - \varepsilon\, r_i,\ r_i + \varepsilon\, r_i), \tag{4}$$

where U denotes a uniform distribution within the specified interval.

3.5 Loss function

We define the loss function in the following form:

$$F(\lambda) = \sum_i L(i)[1 - V(i,\lambda)]d_i + L(i)b_i + V(i,\lambda)u \tag{5}$$

Here, $L(i)$ is defined in (2); $V(i, \lambda)$ is defined in (3); d_i is a random value describing the damage associated with loss of life incurred only in case if landslide occurs and no evacuation was performed; b_i is a random value describing the damage to the buildings and infrastructure; u is the cost of evacuation (constant value; Fig. 7). The loss function $F(\lambda)$ is a random variable depending on the evacuation threshold correction coefficient λ.

3.6 Optimization of evacuation threshold

The threshold for evacuation in the form (3) depends on adjustment coefficient $\lambda \in (0, 1)$, which is an unknown parameter subject to optimization. The objective of the optimization procedure is to minimize expected losses:

$$\min_{\lambda}\ \mathrm{E}[F(\lambda)] \tag{6}$$

Here, $\mathrm{E}[\cdot]$ denotes the expectation of a random value; the function $F(\lambda)$ is defined according to (5). An equivalent formulation of the optimization problem has the following form

$$\min_{\lambda} \sum_i L(i)[1 - V(i,\lambda)]\mathrm{E}[d_i] + V(i,\lambda)u \tag{7}$$

Here, we eliminated the constant $\sum L(i)\mathrm{E}[b_i]$ which does not depend on the adjustment coefficient λ. For the simplification purposes, we assume that there is no seasonal dependence of conditional (on landslide occurrence) expected loss of life induced by a landslide, and hence, can denote $\mathrm{E}[d_i] = v$ (fixed value). Based on that, the problem (7) may be represented in the form

$$\min_{\lambda} \sum_i L(i)[1 - V(i,\lambda)] + V(i,\lambda)\alpha, \quad \text{where } \alpha = \frac{u}{v}. \tag{8}$$

The problem (8) is equivalent to the original problem (6) in terms of optimal value of the adjustment coefficient λ.

4 Model results and sensitivity

In order to completely define the objective function in the optimization problem, it is necessary to define the damage associated with the loss of life and evacuation. For better reflecting reality, we introduce additional constraint on evacuation duration and require an evacuation period to be at least 24 h, meaning that if the value of $V(i, \lambda)$ defined in (3) would turn into 1 for a 6-h period i_0, then at least for the periods i_0, $i_0 + 1$, $i_0 + 2$, and $i_0 + 3$, the people would have been evacuated and would have been located somewhere outside of the dangerous area for that whole 24 h. After that period, if the intensities $\hat{I}_{ij}$ calculated for observed rainfall stay above the evacuation threshold as defined in (3), the people will not return back and will wait until the value $V(i, \lambda)$ drops to zero. We also assume that losses u do not incur per each 6-h interval of evacuation, yet per entire evacuation period (up to 5 days of consecutive series of threshold exceedance). Please note that Eqs. 5, 7, and 8 add sum u to losses per each 6-h interval of evacuation and therefore should be corrected. However, we will not introduce into equations the damage calculation rules verbally described above to avoid unnecessary complexity in formulas. This remark has to be kept in mind when we refer to the simplified Eqs. 5, 7, and 8.

We fixed evacuation cost $u = 10{,}000$ and expected loss of life (total per one landslide) $v = 5{,}000{,}000$ and calculated the expected losses for different values of adjustment parameter λ. These numbers can be considered in US Dollars and represent estimates for a typical situation in the Combeima valley. We simulated rainfall measurements during the period 1991–2000 based on ERA-40 data by introducing random errors according to (4). For values of rainfall measurement error ε in interval [0, 0.3] with step size equal to 0.05, we took 10,000 samples of simulated observations during the entire 10-year period. The results are presented in Fig. 8 (dots indicate minimum expected losses, i.e., optimal value of threshold adjustment). On a separate graph, we present the dependence of optimal expected losses on the rainfall measurement error (Fig. 9). It can be noted that errors in rainfall measurement lead to the exponential growth of expected losses. The dependence of the adjustment parameter λ, and thus the level of adjustment of the evacuation threshold, on the rainfall measurement error is presented in Fig. 10.

An important question connected with the optimization problem (8) is about the influence of a loosely defined constant α on the solution of the problem. We performed several model runs for various values of α and found out that to a certain degree, the optimal evacuation thresholds are insensitive to the values of α. Thus, Fig. 10, representing the decision making rule for evacuation, does not change if the cost of life v increases by 20%. This means that the evacuation thresholds for different levels of observation error and, most importantly, decision-making rules corresponding to the thresholds, are robust against a value, such as the cost of life that is difficult to define.

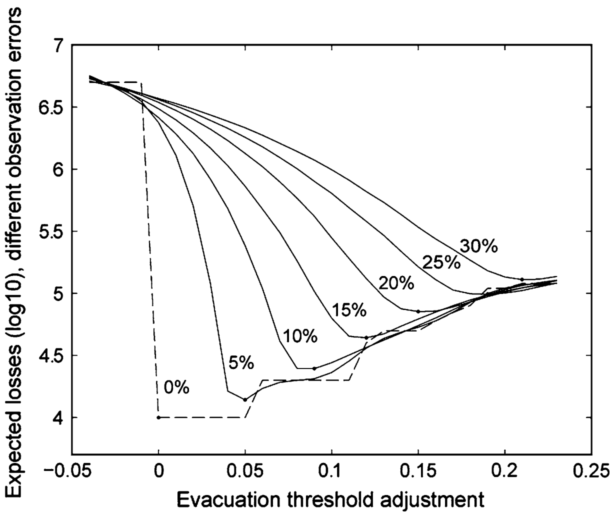

Fig. 8 Expected losses on log10 scale depending on evacuation threshold adjustment for different observation errors (0%, 5%, 10%,…, 30%). *Dots* on the graph indicate optimal values of adjustment, i.e., delivering minimal expected losses for given observation error

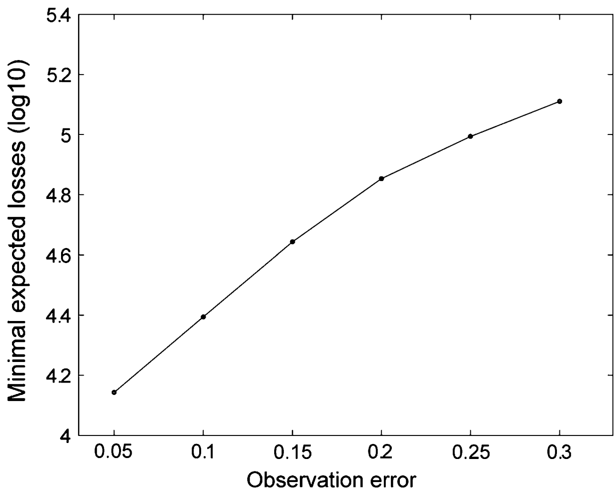

Fig. 9 Dependence of minimal expected losses (log10 scale) on the rainfall measurement error

5 Discussion and implications for landslide EWS

The approach developed in our model is based on stochastic optimization (Spall et al. 2006) with application to variable rainfall measurement errors and relevant evacuation thresholds, which has barely been applied to landslide problems so far. In landslide research, it is therefore rather uncommon to link measured environmental parameters such as rainfall with landslide consequences and damage in one integrated model. The approach has clear limitations but also significant potential that may lead well beyond what we have

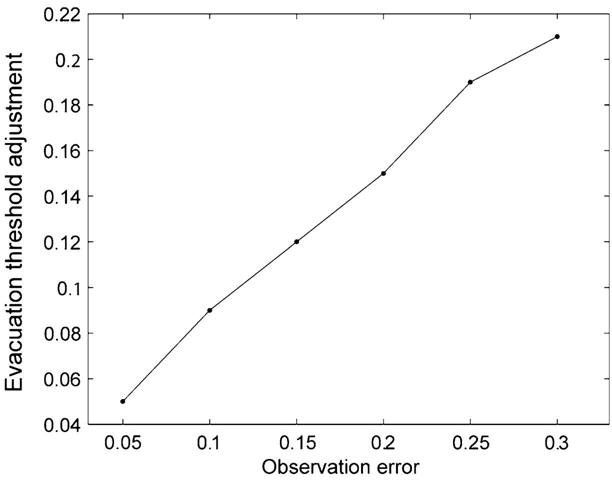

Fig. 10 Dependence of the evacuation threshold adjustment on the rainfall measurement error

presented here. The experience with first model development and simulations, and the implications for landslide research and risk management, is summarized in the following.

An integrated landslide EWS model of the kind presented in this study needs to make important simplifications to natural and human-based processes. Well aware of the current limitations in data and process understanding, we aimed at developing a model that has a basis in real world cases (Colombia) and at the same time provides an adequate theoretical background to allow for general conclusions on landslide EWS.

Rainfall observation errors are a very widespread problem in landslide EWS practice. The problem is serious because rainfall measurements are typically a core source of information for subsequent decisions on issuing warnings or ordering evacuation. The model results allow us to address the initially outlined research question on the effect of rainfall measurement errors on the extent of damage due to landslides. The results suggest that a linearly increasing observation error implies an exponentially rising loss due to landslides. These findings are also essential in the context of current initiatives in ground- and space-based earth observation (Fritz et al. 2008; Hong et al. 2006; Khabarov et al. 2008; Williamson et al. 2002).

In the presented model's setup, we use a deterministic intensity–duration landslide-triggering threshold. This relation was derived empirically with application of statistical methods based on the records of measured rainfall and registered landslide occurrence and hence includes related uncertainties. Therefore, randomization of the triggering threshold could potentially improve the model and bring it closer to reality. An implementation of a suitable approach to perform the threshold randomization based on reliable data could be a promising direction for future research.

An important question of practical relevance is whether the investment in more rainfall gauges would be worth, considering the potential benefit from loss reduction. Our model results can be an indication for such cost–benefit considerations. However, since the model is spatially not explicit, no answer is provided where the new gauges should be located to minimize the observation error. As the implementation of the EWS in the Combeima Valley has shown, there are several restrictions to find optimal sites for rainfall gauges. These include uncertainties in rainfall variation in space and time, extreme topography and access for maintenance, the acceptance by the local population, and problems with illegally armed groups. Realistic solutions usually imply a trade-off between such factors. In this context, the new findings from our model can be important for finding optimal investment solutions with government officials and donors in terms of effective disaster prevention.

Another important aspect evaluated in the model refers to the second research question, i.e., the importance of landslide-triggering rainfall thresholds for loss reduction. In our model, the decision on evacuation is solely based on the rainfall threshold. This is to some degree a simplification of the reality since an optimally designed landslide EWS should have a redundancy, e.g., local observers that report back to the EWS center, geophones, or additional sensors measuring parameters such as pore pressure in the soil, etc. However, to be able to provide straightforward conclusions on the effect of thresholds, we did not include any other parameters.

Our model indicates that to some degree, adverse effects by rainfall observation errors can be attenuated by adjusting the threshold. Systematic variation and optimization of the adjustment coefficient λ, based on 10,000 model simulations suggests that for a particular observation error and a threshold adjustment, a minimum expected loss can be found (Figs. 8, 10). The larger the observation error, the stronger should be the threshold adjustment. Results furthermore show that increasing the adjustment may have a negative impact in terms of expected losses.

These results are important for the design of evacuation decision-making procedures (Whitehead 2003). However, for a direct application to EWS practice, it should be considered that the model ignores any psychological "cost," i.e., evacuations in vain have only the relatively low cost in monetary terms. Increasing resistance by local population to evacuate with repeated evacuations without significant landslide events are thus not considered. In order to include this aspect in the model, more research is needed because people's response to warnings is generally complex. Dow and Cutter (1998), for instance, have shown that the likelihood of people responding to a warning is not reduced by the so-called "cry-wolf" syndrome if the basis of the false alarm is understood.

The values defined for the cost of evacuation (USD 10,000) and average total loss of life (USD 5 millions) are estimated for a typical situation in the Combeima valley, for a town potentially affected by a landslide. The number for loss of lives is based on a scenario of loss of 10 lives, where one life is set equal to USD 0.5 million. Defining a monetary value for life can be controversial from an ethical point of view but is a common practice in risk management for cost–benefit analyses of hazard protection and prevention measures. An advantage of our model in this context is that we were able to show that the adjustment of the evacuation threshold is to a certain degree not sensitive to the absolute value of loss of life.

An alternative approach to cost optimization would be the implementation of risk-based criterion such as cost minimization conditioned on admissible level of value-at-risk, where evacuation costs are strictly separated from loss of life instead of weighting loss of life in monetary terms. Moving into this direction and comparison with the present approach would be useful for better understanding the guiding principles the EWS should be based upon.

This study is a first step for an integrated numerical modeling of EWS that allow the investigation of aspects that have not been studied systematically so far. For future research in this field, we suggest the transformation to a spatially explicit model to study in more details the spatial aspects of EWS. Another step could be the introduction of the dependence of damage on landslide magnitude. Ideally, this should be based on magnitude–frequency relations of landslides which have gained substance with the analysis of quantitative landslide observations (e.g., Hovius et al. 1997; Crozier and Glade 1999). In principle, it has been found that the relation is a power law corresponding to the Gutenberg–Richter law for earthquakes (Dai and Lee 2001; Hungr et al. 2008). In order to establish an adequate relation for a particular region, a reasonable number of quantitative landslide observations is necessary. In this respect, a drawback for Colombia currently exists due to only few quantitative records available on landslide magnitude.

6 Conclusions

In many regions of the world, landslides cause billions of dollars of damage and often imply significant death rates (Keefer and Larsen 2007). Colombia is one of the particularly badly affected countries due to predominantly rugged terrain and tropical rainfall conditions. In many areas, landslide hazard zones overlap with residential zones and infrastructure. EWS are therefore important to reduce landslide risks, and in particular, avoid casualties. However, design, implementation, and successful operation of a landslide EWS is complex and has rarely been achieved. A critical problem is uncertainties related to landslide triggering conditions.

We have described here the recent implementation of a landslide EWS for a hotspot area in Colombia: the Combeima valley. As in many other cases, an insufficient basis of data (rainfall, soil measurements, landslide event record) and the aforementioned uncertainties represent an important complication. To be able to better assess the influence of the different EWS components, we developed a numerical model that simulates the EWS in a simplified yet integrated way.

Results show that a linearly increasing rainfall observation error implies a nearly exponential rise in damage cost. These considerations can help finding improved cost–benefit solutions for rainfall monitoring stations. We furthermore investigated uncertainties related to the rainfall landslide-triggering threshold, typically a key element for evacuation decisions. Stochastic optimization suggests an increasing adjustment of the threshold with increasing observation error. This essentially means that, in the future, not a fixed rainfall threshold would be used but rather one within a range of adjustment according to the local observation quality.

As we have seen with the practical EWS implementation in the Combeima valley, the success is also highly dependent on aspects such as institutional coordination, emergency protocols, or acceptance of the EWS by the local population. Nevertheless, our modeling studies are a first step toward a more generic and integrated approach that bears important potential for substantial improvements in design and operation of landslide EWS.

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